

Discriminator optimal transport

Akinori Tanaka (RIKEN AIP/iTHEMS, Keio Univ.)
@NeurIPS2019, Vancouver, Canada.

Motivation I

- Generative Adversarial Networks (Goodfellow et al. 2014) is a well known DL scheme for generating images.
- Even if we succeed in training, there are two problems:
 1. Usually, the discriminator after the training is discarded. It sounds wasteful.
 2. The generated images sometimes include unwanted structures.
- The problem 2 may be relaxed by solving the problem 1, i.e. by recycling the trained discriminator.

Motivation 2

There are some known works in the same spirit:

- Discriminator Rejection Sampling (Azadi et al. 2018)

The ideal discriminator $D(x) = \frac{1}{1 + \left(\frac{p_G(x)}{p(x)}\right)} \Rightarrow$ Rejection sampling for $G(z)$

- Metropolis-Hastings GAN (Turner et al. 2018)

The ideal discriminator $D(x) = \frac{1}{1 + \left(\frac{p_G(x)}{p(x)}\right)} \Rightarrow$ Metropolis-Hastings test for $G(z_1) \rightarrow G(z_2) \rightarrow \dots$

SLOGAN: “Reject if $D(G(z))$ is too small.”

These are **passive** methods to improve generated images.

Is it possible to take an “**active**” method, somehow ?

Our proposal

- Discriminator Optimal Transport (DOT)

SLOGAN: “Deform $G(z)$ so that $D(G(z))$ is large.”

Target space DOT

$$\operatorname{argmin}_x \left\{ ||x - G(z_y)||_2 - D(x) \right\}$$

Latent space DOT

$$\operatorname{argmin}_z \left\{ ||z - z_y||_2 - D(G(z)) \right\}$$

- ✓ These have theoretical background from GAN’s objective and OT theory.
- ✓ These can be implemented by gradient descent, i.e. backprop, and GPU friendly.
- ✓ These do improve scores like EMD, IS and FID.

For more detail, please come to our poster!
We are looking forward to discuss with you!